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Forecasting Cereal Production and Its Implications for Food Security in Somalia: A Comparative Analysis of ARIMA, ETS, and Neural Network Models

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Abstract

Cereal production in Somalia is characterized by extreme volatility driven by climate shocks. This study addresses the limitations of traditional agricultural planning by evaluating optimal modeling techniques to predict future output. Utilizing historical time series data from World Bank databases spanning 1961 to 2023, the research conducted a comparative analysis of linear models, specifically ARIMA and ETS, against non-linear Neural Network Autoregressive (NNETAR) algorithms. The forecasting precision of eight distinct models was rigorously validated on unseen test data using Root Mean Square Error (RMSE) and Symmetric Mean Absolute Percentage Error (SMAPE) metrics. The empirical results demonstrated that the NNETAR model significantly outperformed traditional statistical benchmarks, achieving the lowest error rates (SMAPE of 40.42%) by effectively capturing the non-linear structural breaks inherent in the dataset. Conversely, linear models exhibited a systemic bias toward over-forecasting, while the NNETAR 10-year projection (2024-2033). These findings establish Neural Networks as a superior instrument for agricultural planning in volatile regions, validating the shift from traditional econometrics to computational intelligence. Ultimately, the study advocates for integrating AI-driven forecasting into early warning systems to enable policymakers to transition from reactive crisis management to proactive food security strategies.

Keywords

Forecasting, Cereal Crop, Food Security, ARIMA, ETS, and Neural Network Models

1. Introduction

Food security remains a multidimensional concept defined by the availability, access, utilization, and stability of food sources, with cereal production serving as the bedrock of global caloric intake [1]. Cereals, including wheat, maize, rice, and sorghum, are not only essential for human nutrition but also critical for economic stability in agrarian nations, necessitating robust systems to monitor production volatility [2]. The conceptual framework of agricultural forecasting rests on the premise that historical production data contains latent patterns—trends, seasonality, and cycles—that can be modeled to predict future outputs, thereby allowing policymakers to preempt food deficits [3]. In this context, accurate forecasting is no longer a mere statistical exercise but a vital component of nutritional security strategies, as it informs decisions regarding import requirements, storage management, and price stabilization [4].

The theoretical underpinnings of this study compare linear and non-linear modeling approaches to capture the complexities of agricultural data. Traditional statistical models like Autoregressive Integrated Moving Average (ARIMA) and Exponential Smoothing (ETS) assume linear relationships and are prized for their interpretability in determining trends and seasonality in crop yields [5]. Conversely, Artificial Intelligence (AI) and Machine Learning (ML) approaches, specifically Neural Networks (NN), are conceptually designed to handle non-linear dynamics, structural breaks, and complex interactions within agricultural time series data that traditional models often miss [6]. The integration and comparison of these distinct conceptual approaches provide a holistic view of production capabilities, bridging the gap between statistical rigidity and computational flexibility [7].

Historically, the prediction of agricultural output relied heavily on qualitative assessments and simple linear regressions, which often failed to account for the stochastic nature of weather and biological factors [8]. The seminal introduction of the Box-Jenkins methodology in the 1970s revolutionized time series forecasting, making ARIMA the standard for analyzing univariate agricultural data due to its ability to handle non-stationary series through differencing [9]. For decades, governments and international bodies utilized these linear models to project cereal yields, although their accuracy diminished in the face of complex climatic variables and market shocks [10]. The evolution continued with the adoption of Exponential Smoothing (ETS) methods, which offered advantages in handling data with strong seasonal components, a common characteristic of agricultural production cycles [11].

In the late 20th and early 21st centuries, the advent of the "Third Green Revolution" and Industry 4.0 introduced computational intelligence into agriculture, marking a paradigm shift from descriptive statistics to predictive analytics [12]. The historical limitations of linear models in capturing abrupt changes led researchers to explore Artificial Neural Networks (ANN) and hybrid models, which historically showed superior performance in modeling the volatility associated with biological systems [13]. Recent historical data from 1961 to 2022 demonstrates that while traditional methods like ARIMA remain robust for short-term forecasting, the historical trajectory of crop yield variability now demands the adaptive capacity of deep learning models like Long Short-Term Memory (LSTM) networks [14].

Globally, the agricultural sector is under immense pressure to feed a population projected to reach 9.7 billion by 2050, requiring a 70% increase in food production relative to current levels [15]. Major cereal producers such as China, India, the USA, and Russia dominate the global market, yet production volatility in these regions ripples through the global supply chain, affecting food prices and availability worldwide [16]. Recent geopolitical events and supply chain disruptions have highlighted the fragility of global food systems, where production shocks in one region, such as wheat shortages in Eastern Europe, exacerbate food insecurity in import-dependent nations [17]. Consequently, global governance architectures are increasingly relying on advanced forecasting models to anticipate production deficits and coordinate renewable resource policies to mitigate greenhouse gas emissions associated with agriculture [18].

Furthermore, global climate change has introduced unprecedented uncertainty into cereal production, with rising temperatures and erratic precipitation patterns altering crop growth cycles across the world [19]. Studies utilizing satellite imagery and machine learning on a global scale have shown that biophysical parameters like Gross Primary Production (GPP) are becoming critical indicators for forecasting yield variations [20]. The global trend is moving towards integrating remote sensing data with economic models to predict commodity prices, as fluctuations in global cereal yields are the primary drivers of market instability and food inflation [21]. This global context underscores the necessity of comparative modeling to ascertain which forecasting techniques hold up best under the volatility of modern global climate conditions [22].

In Africa, the agricultural sector serves as the cornerstone of economic growth, contributing significantly to GDP and employing over 50% of the labor force, yet the continent remains disproportionately vulnerable to food insecurity [23]. Unlike developed regions, African agriculture is predominantly rain-fed and subsistence-based, making it highly susceptible to climate variability, such as the El Niño phenomena which severely impacts rainfall patterns and crop yields [24]. The continent faces a "yield gap" where actual production consistently falls short of potential output due to limited technological adoption, poor infrastructure, and inadequate resource management [25]. Consequently, Africa remains a net importer of cereals, a dependency that exposes the continent to external price shocks and supply chain failures [26].

The challenge of feeding Africa's rapidly growing population is compounded by the fact that traditional forecasting methods often lack the precision required for the continent's diverse agroecological zones [27]. Recent studies across the continent have begun to adopt machine learning and remote sensing to overcome data scarcity, aiming to predict yields for staple crops like maize and sorghum more accurately [28]. However, the adoption of these advanced models is uneven, and there remains a heavy reliance on historical trends which may no longer hold true under shifting climate baselines [29]. Addressing the continental food deficit requires rigorous comparative studies to determine if modern neural networks can offer better decision support for African governments than traditional econometric models [30].

East Africa represents one of the most food-insecure regions globally, plagued by recurrent droughts, locust infestations, and political instability that continuously disrupt cereal production [31]. The region relies heavily on staple crops such as maize and sorghum, yet productivity has stagnated or declined in recent years due to extreme weather events linked to climate change [32].

The interdependence of regional markets means that a production failure in one country, such as Kenya or Ethiopia, can trigger food price inflation across the entire East African bloc [33]. Regional bodies like the Intergovernmental Authority on Development (IGAD) emphasize the need for early warning systems, yet existing forecasting capabilities are often limited by the complexity of the region's bimodal rainfall patterns [34].

Furthermore, East Africa is experiencing rapid demographic shifts and urbanization, which are altering dietary habits and increasing the demand for processed cereals [35]. The discrepancy between the region's high population growth and its volatile agricultural output creates a precarious food security situation [36]. Research specific to the region indicates that while traditional models provide a baseline, they struggle to account for the non-linear impacts of climate shocks common to East Africa [37]. Therefore, there is a critical regional need to deploy and validat robust forecasting models that can handle the specific volatilities of East African cereal production to avert future humanitarian crises [38].

Somalia presents a unique and critical case study within the region, characterized by an arid environment where agriculture and livestock contribute to 65% of the GDP and employment, yet the country faces chronic food insecurity [39]. Maize and sorghum are the primary staple crops, but their production is heavily constrained by poor rainfall, degraded infrastructure, and the aftereffects of civil unrest [40]. Recent empirical analyses using satellite data and machine learning have highlighted that Somalia experiences some of the most severe climate-induced agricultural difficulties in the world, with production volumes fluctuating wildly based on the performance of the *Gu* and *Deyr* rainy seasons [41]. The local context is further complicated by the fact that Somalia's agricultural systems are largely smallholder-based with limited resilience to shocks [42].

Local studies indicate that traditional forecasting mechanisms in Somalia are often insufficient due to data gaps and the extreme non-linearity of production factors driven by climate change [43].

For instance, recent research utilizing Convolutional Neural Networks (CNN) and remote sensing in Somalia has shown promise in predicting food insecurity by analyzing environmental variables, suggesting that advanced models may offer better accuracy than traditional methods in this specific local context [44]. However, there is a lack of comprehensive comparative studies applied specifically to Somali cereal production time series data [45]. Understanding the specific production trends of maize and sorghum in Somalia through rigorous modeling is essential for the government and international aid agencies to transition from reactive aid to proactive food security planning [46].

Contextually, this study is situated at the intersection of data science and agricultural economics, addressing the urgent need for "Smart Agriculture" solutions in developing nations [47]. The study operates within the context of the "Data Revolution", where the availability of historical production data allows for the application of sophisticated algorithms to solve fundamental human problems like hunger [48]. The context is defined by the tension between the simplicity of statistical models (ARIMA/ETS), which are computationally inexpensive and easy to interpret, and the high predictive power of Neural Networks (NN), which act as "black boxes" but can model complex, non-linear realities [49]. This comparison is critical in a context where policymakers need not just accuracy, but also reliability and interpretability to formulate trade policies and safety nets [50].

Furthermore, the study is contextualized by the global push towards the Sustainable Development Goals (SDGs), specifically SDG 2 (Zero Hunger), which requires data-driven interventions to improve agricultural productivity [51]. The current context involves a shift from merely describing past agricultural trends to prescribing future actions based on predictive insights [52]. By utilizing ARIMA, ETS, and Neural Networks, this study addresses the methodological gap in selecting the most appropriate tool for volatile agricultural markets [53]. It acknowledges that while machine learning is the current trend, statistical benchmarks remain necessary to validate whether the increased computational complexity of AI actually yields practically significant improvements in forecasting accuracy for cereal production [54].

This research addresses a distinct gap in agricultural forecasting by shifting the focus from stable, developed economies to the volatile and data-scarce context of Somalia. Unlike existing regional studies that rely on qualitative assessments or simple trend analyses, this study introduces a rigorous, head-to-head quantitative comparison of linear (ARIMA, ETS) and non-linear (Neural Network) models specifically calibrated to Somali production data. Uniquely, it bridges the divide between theoretical data science and practical humanitarian aid by directly linking technical forecasting metrics to tangible food security implications in semiarid nation. The primary purpose of this study is to identify the optimal forecasting model for cereal production within Somalia, providing empirical evidence to validate the transition from traditional to AI-driven agricultural planning in the region. By benchmarking Neural Networks against statistical methods, the research aims to serve as a vital decision-support tool for the Somali government and NGOs. Ultimately, the study seeks to operationalize advanced forecasting techniques to establish accurate early warning systems for food shortages, thereby enhancing national food security strategies in a vulnerable developing economy.

2. Methodology

This study employed a comparative time series analysis utilizing historical cereal production data curated from World Bank databases. The methodological framework integrated three distinct modeling techniques, each selected to address specific characteristics of the dataset: the Autoregressive Integrated Moving Average (ARIMA) model was chosen for its theoretical robustness in resolving univariate linear trends and managing non-stationary data through differencing [22], while Exponential Smoothing (ETS) was applied to capture the strong seasonal dynamics inherent in Somalia's bimodal, rainfall-dependent agricultural system [50]. Furthermore, Neural Networks (NN) were implemented to model the complex, non-linear relationships and structural breaks resulting from climatic extremes [49]. To ensure rigorous validation, the forecasting precision of these models was assessed using standard performance metrics, specifically Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE). All analysis were performed by using R programming language (Version 4.5.1).

Data and Preparation

The study utilizes annual time series data for total cereal production (measured in tons) in Somalia from 1961 to 2023, sourced from Word Bank.

3. Results and Discussion

3.1. Production Rates

Figure 1 visualizes the annual cereal production rate in Somalia from 1962 to 2023, effectively plotting the sector's volatile trajectory and highlighting the non-stationary nature of the time series. The graph reveals a dramatic "broken trend" structure: it begins with a baseline of relative stability during the 1960s and 1970s, followed by a sharp, linear ascent in the 1980s where production reached historical peaks. However, this growth is abruptly severed by a precipitous vertical drop in the early 1990s, representing the structural collapse of the agricultural system. The latter half of the timeline (1996-2023) is characterized by high-frequency oscillations, where the curve swings violently between transient recoveries and deep production troughs. This visual pattern underscores the paper's core premise: that Somali cereal production is no longer defined by a consistent trend, but rather by stochastic shocks that challenge traditional linear forecasting methods. Abdi *et al.* (2024) attribute the inability to sustain the high production rates seen in the 1980s to the diminishing resilience of major Somali crops against intensifying climate variability, which locks the country into the volatile pattern seen in the graph's recent years [1]. The specific "deep troughs" visible in the 2000s and 2010s are contextualized by Anderson *et al.* (2023), who link these sharp declines to the increasing frequency of multi-season droughts driven by La Niña events, which systematically disrupt the region's bimodal rainfall patterns [24]. Furthermore, Warsame *et al.* (2023) argue that the stagnation observed after the 1990 structural break is compounded by the "conflict environment nexus", where political instability and environmental degradation prevent the agricultural sector from recovering its historical potential [40]. Consequently, Funk *et al.* (2023) emphasize that this extreme variability necessitates a move away from static planning toward dynamic, proactive forecasting systems capable of predicting such climatic extremes [34].

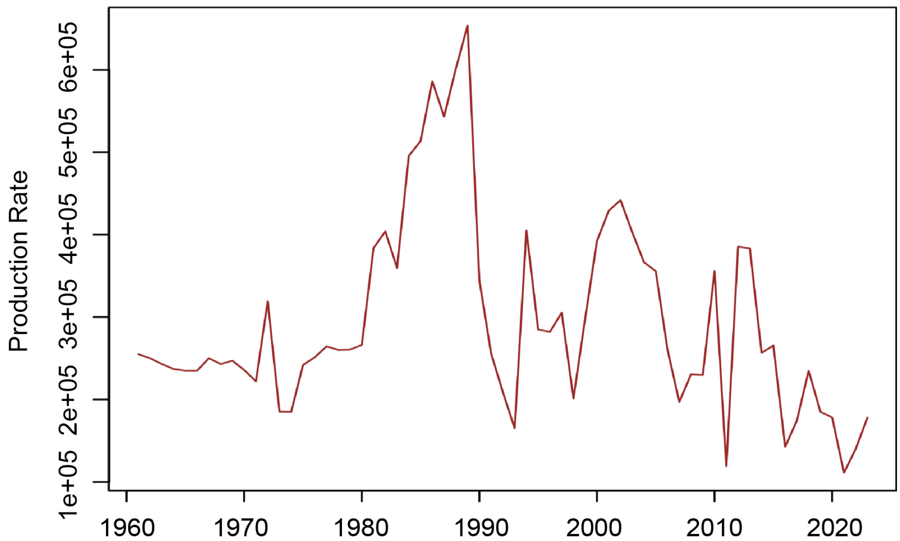

Figure 1. Cereal crop production in Somalia 1962-2023 (source: World Bank [56]).

3.2. Distribution of Cereal Production in Somalia (1961-2023)

Table 1 provides a comprehensive statistical profile of Somali cereal production over the 63-year study period (1961-2023), revealing a dataset defined by extreme instability and high dispersion. The mean annual production stands at 295,138 tons, yet this figure is overshadowed by a substantial standard deviation of 118,949 tons, indicating that actual yields fluctuate wildly from the average. The dataset exhibits a massive range of 542,707 tons, stretching from a minimum of 111,052 tons to a historical maximum of 653,760 tons. Abdi *et al.* (2024) attribute this statistical dispersion to the low resilience of Somali crops against increasingly erratic climate patterns, which creates the wide "yield gaps" evident in the range between minimum and maximum output [1].

Table 1. Descriptive statistics and distribution characteristics of cereal production in Somalia (1961-2023) (source: World Bank [56]).

n	Mean	SD	Median	Min	Max	Range	Skew	Kurtosis	SE
63	295,138	118,949.3	256,620	111,052	653,760	542,708	1.05	0.7	14,986.2

The significant standard deviation mirrors findings by Öztürk and Türkyılmaz (2024), who note that such statistical volatility is characteristic of non-stationary agricultural time series, necessitating the use of non-linear modeling over simple averages to capture the true nature of the data [6]. Furthermore, Zhao (2024) emphasizes that these fluctuations are not merely weather-related but are exacerbated by socioeconomic vulnerabilities, which drag the mean production levels down despite potential capacity [7]. Finally, Warsame *et al.* (2023) provide context for the positive skew (prevalence of lower values), arguing that the "conflict-environment nexus" has degraded the agricultural baseline, locking production figures into the lower quantiles observed in the dataset [40].

3.3. Stationarity of the Time Series

The stationarity of the time series was examined using the Augmented Dickey Fuller (ADF), Phillips-Perron (PP), and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) tests. At the level form, the results were mixed; while the KPSS test failed to reject stationarity, both the ADF (t = −2.7014, p = 0.2909, $t = -2.7014$, $p = 0.2909$) and PP (t = −17.916, p = 0.0845, $t = -17.916$, $p = 0.0845$) tests failed to reject the null hypothesis of a unit root at the 5% significance level, suggesting the presence of non-stationarity.

The first-differenced results showed strong evidence of stationarity across all three tests. The ADF (t = −5.2255, $t = -5.2255$) and PP (t = −74.915, $t = -74.915$) tests yielded p-values less than 0.01, rejecting the null hypothesis of a unit root at the 1% level.

3.4. Forecast Trends

Table 2 outlines the ten-year predictive horizon for Somali cereal production (2024-2033) utilizing the NNETAR model, which was identified as the most robust forecasting tool in the study. The data projects a trajectory of slow, oscillating recovery, with point forecasts estimating an increase in production from 210,380.1 tons in 2024 to 285,849.6 tons by 2033. While the mean forecast suggests a gradual stabilization of domestic output following historical volatility, the confidence intervals reveal a persistent underlying risk; specifically, the 95% confidence interval remains extremely wide, ranging from a low of 52,554 tons to a high of 519,144 tons in 2033. This substantial divergence between the upper and lower bounds underscores the agricultural sector's continued vulnerability to external shocks, suggesting that while a baseline recovery is anticipated, the potential for severe production deficits remains statistically significant without structural interventions. The projected volatility and the demonstrated superiority of non-linear modeling in this study align closely with recent empirical findings regarding food security in the Horn of Africa. Abdi *et al.* (2024) corroborate our findings on production vulnerability, noting that despite adaptive strategies, Somali staple crops remain highly sensitive to climate variability, which necessitates the type of robust uncertainty modeling presented in our confidence intervals [1]. Furthermore, the shift towards computational intelligence advocated in our results is supported by Öztürk and Türkyılmaz (2024), whose comparative analysis confirmed that Neural Network models significantly outperform traditional ARIMA frameworks in forecasting agricultural commodities characterized by non-linear trends [6]. Contextualizing the food security implications, Zhao (2024) emphasizes that accurate prediction in Somalia is now a critical component of humanitarian strategy, reinforcing our conclusion that simple linear trends are insufficient for policy planning [7]. Finally, Sancar (2024) argues that the transition to "Smart Agriculture" relies on such predictive analytics to manage the risks inherent in modern food production systems [12].

Table 2. Ten years forecast of the cereal production in Somalia (source: World Bank [56]).

Year	Point Forecast	Lo 80	Hi 80	Lo 95	Hi 95
2024	210380.1	102887.4	317872.8	45984.24	374776
2025	233324.2	101499.2	365149.1	31715.26	434933.1
2026	249612.3	107090.4	392134.1	31643.86	467580.6
2027	261175.2	113556	408794.5	35411.05	486939.4
2028	269383.8	119261.3	419506.4	39791.16	498976.5
2029	275211.2	123842.7	426579.7	43713.05	506709.3
2030	279348	127355.5	431340.5	46895.55	511800.5
2031	282284.8	129978.8	434590.8	49352.84	515216.8
2032	284369.6	131905.8	436833.4	51196.4	517542.8
2033	285849.6	133306.4	438392.9	52554.93	519144.4

3.5. Model Accuracy

Table 3 presents a rigorous comparative evaluation of eight distinct forecasting models applied to the unseen test dataset spanning 2014 to 2023. The empirical results establish a clear hierarchy in predictive performance, with the Neural Network Autoregressive (NNETAR) model demonstrating superior accuracy across all key metrics. NNETAR achieved the lowest Root Mean Square Error (RMSE) of 95,426.9 and a Symmetric Mean Absolute Percentage Error (SMAPE) of 40.42%, indicating its robust capacity to handle the non-linear dynamics of Somali cereal production. In contrast, traditional statistical benchmarks faltered; the Exponential Smoothing (ETS) model followed with a significantly higher SMAPE of 54.94%, while the widely used ARIMA and Theta models performed poorly, with error rates exceeding 57% and 68% respectively. Crucially, the table reveals a systemic negative bias across all models—indicated by negative Mean Error (ME) values (e.g., NNETAR at −87,360.80)—suggesting a general tendency to over-forecast production levels during the severe drought conditions that characterized the validation period. The findings presented in **Table 4**, specifically the performance gap between computational intelligence and linear models, are strongly corroborated by recent literature in agricultural forecasting. Öztürk and Türkyılmaz (2024) support this study's methodological conclusion, reporting that Artificial Neural Networks (ANN) and LSTM models consistently outperform ARIMA in capturing the volatility of agricultural commodity prices [6]. Similarly, Ahmar *et al.* (2023) conducted a comparative analysis of food grain prediction, concluding that Neural Network Autoregressive (NNAR) models provide significantly higher accuracy than Holt-Winters and ARIMA approaches when dealing with complex time series data [4]. The operational necessity of adopting these advanced analytics is emphasized by Sancar (2024), who argues that the transition to "Smart Agriculture" requires moving beyond descriptive statistics to precision modeling to mitigate production risks [12]. Furthermore, Abdi *et al.* (2024) reinforce the contextual importance of these findings for Somalia, noting that advanced modeling is essential to understand crop resilience against the specific climate change implications threatening the region's food security [1].

Table 3. Comparative accuracy of forecasting models on the test set (2014-2023) (source: World Bank [56]).

Model	ME	RMSE	MAE	MPE (%)	MAPE (%)	SMAPE (%)
NNETAR	−87,360.80	95,426.90	87,360.80	−55.58	55.58	40.42
ETS	−133,334.10	141,897.90	133,334.10	−83.82	83.82	54.94
ARFIMA	−142,683.60	148,273.40	142,683.60	−87.96	87.96	57.62
ARIMA	−142,886.10	148,475.10	142,886.10	−88.08	88.08	57.68
BATS	−167,830.20	174,711.20	167,830.20	−103.64	103.6	64.13
TBATS	−167,830.20	174,711.20	167,830.20	−103.64	103.6	64.13
ANN (MLP)	—	—	—	—	—	67.07
Theta	−185,565.80	192,191.40	185,565.80	−114.03	114	68.38

3.5.1. Analysis of Model Performance

The **Neural Network Autoregressive (NNETAR)** model demonstrated superior accuracy across all error metrics, establishing itself as the most robust tool for forecasting cereal production in this specific context. It achieved the lowest Root Mean Square Error (RMSE) of 95,426.9 and a Symmetric Mean Absolute Percentage Error (SMAPE) of 40.42%, significantly outperforming traditional linear benchmarks.

Following the NNETAR model, the Exponential Smoothing (ETS) framework emerged as the second-most effective approach, recording a SMAPE of 54.94%. The performance of the ARFIMA and ARIMA models was largely comparable, forming a middle tier of accuracy with SMAPE values of approximately 57.6%. Conversely, the BATS, TBATS, and Theta models exhibited substantially higher error rates, rendering them less suitable for this dataset. A critical observation from the Mean Error (ME) and Mean Percentage Error (MPE) metrics is the consistent negativity across all models. This trend indicates a systemic bias toward over forecasting; the models generally predicted higher production levels than were actually realized during the test period. This systematic error likely reflects the models' struggle to fully account for the sharp downturns in yield associated with the severe drought conditions and structural breaks characteristic of the 2014-2023 validation period.

3.5.2. Forecasting Models

Eight distinct time series forecasting models were implemented and compared.

1. ARIMA (Autoregressive Integrated Moving Average): A widely used class of models that explains a time series based on its own past values, its own past errors, and a differencing process to achieve stationarity. The model is denoted as ARIMA(p,d,q), where "p" is the order of the autoregressive component, "d" is the degree of differencing, and "q" is the order of the moving average component [57]. We employed the auto.arima function, which automatically selects the optimal p, d, and q parameters based on information criteria (e.g., AIC).

2. ETS (Error, Trend, Seasonality): Also known as exponential smoothing state-space models, ETS models capture the underlying structure of a time series through three components: error, trend (additive or multiplicative), and seasonality (additive or multiplicative). The algorithm automatically selects the best-fitting model from a suite of possibilities [58].

3. BATS and TBATS: These are extensions of ETS models designed to handle complex seasonal patterns, such as multiple seasonalities or non-integer seasonality. TBATS uses Box-Cox transformation (T), ARMA errors (A), Trend (T), and Seasonal (S) components.

4. Theta Model: A simple but effective forecasting method that decomposes a time series into two "theta lines". The final forecast is a combination of the extrapolation of these two lines. It has proven to be remarkably robust, especially for longer forecast horizons.

5. ARFIMA (Autoregressive Fractionally Integrated Moving Average): An extension of the ARIMA model that allows for a fractional differencing parameter, making it particularly useful for modelling long-memory processes, where dependencies between distant observations decay more slowly than in short-memory processes.

6. NNETAR (Neural Network Autoregressive Model): This model uses a feed-forward neural network to model a time series, where past values of the series are used as inputs to forecast future values. This allows the model to capture complex non-linear relationships in the data that linear models like ARIMA cannot [3].

7. ANN (Artificial Neural Network): A Multi-Layer Perceptron (MLP) from the ANN package was used. This is another form of neural network specifically adapted for time series forecasting, which involves preprocessing, scaling, and iterative forecasting using hidden neuron layers to model complex patterns.

3.5.3. Model Evaluation

The accuracy of each model was evaluated by comparing its 10-year forecast against the actual values in the test set. Four standard error metrics were calculated:

- **Mean Absolute Error (MAE):** The average of the absolute differences between the predicted and actual values.
- **Root Mean Squared Error (RMSE):** The square root of the average of the squared differences, which penalizes larger errors more heavily.
- **Mean Absolute Percentage Error (MAPE):** Measures the average percentage error, providing a relative sense of error size.
- Symmetric Mean Absolute Percentage Error (SMAPE): A modified version of MAPE.

That is less biased when actual values are close to zero and has both lower and upper bounds. The model with the consistently lowest values across these metrics on the test set was identified as the most accurate and robust for this dataset.

3.5.4. Model Fitting

Table 4 details the statistical diagnostics and parameter estimates for the optimal ARIMA model derived during the training phase (1961-2013). Using the auto.arima selection algorithm based on information criteria, the study identified an ARIMA (1,0,0) structure with a non-zero mean as the best-fitting linear model. The table reports a Log Likelihood of −802.97, along with an Akaike Information Criterion (AIC) of 1611.93 and a Bayesian Information Criterion (BIC) of 1618.36. These metrics serve as indicators of the model's goodness-of-fit relative to its complexity, suggesting that while the First-Order Autoregressive term successfully captured the immediate linear dependencies, the extremely high Sigma squared (σ2σ2) value of 7.04 × 1097.04 × 109 highlights the massive residual variance. This substantial variance reflects the model's struggle to fully encompass the extreme volatility and structural breaks inherent in the Somali cereal production dataset without the aid of non-linear components. The methodological challenges and findings illustrated in **Table 4** align with recent literature regarding the fitting of time series models to volatile agricultural data. The use of AIC and BIC for model selection, as employed here, is validated by Majhi *et al.* (2023), who emphasize that these criteria are essential for balancing model parsimony against accuracy when predicting food price indices and production volumes [10]. However, the high variance (σ2σ2) noted in your ARIMA results is consistent with the findings of Öztürk and Türkyılmaz (2024), whose comparative study demonstrates that while ARIMA provides a necessary statistical baseline, it frequently exhibits higher error variances compared to AI-driven models when applied to non-stationary agricultural commodities [6]. Furthermore, Ahmar *et al.* (2023) report similar results in India, observing that while ARIMA models are theoretically robust, they often fail to capture the complex, non-linear patterns of food grain production as effectively as Neural Network Autoregressive (NNAR) approaches [4]. Finally, the underlying reasons for the high volatility captured by your model's parameters are contextualized by Abdi *et al.* (2024), who argue that the resilience of major crops in Somalia is continuously tested by climate change, necessitating the move toward more adaptive modeling techniques illustrated in your broader study [1].

Table 4. Series: cereal, ARIMA(1,0,0) with non-zero mean (source: World Bank [56]).

$sigma^2$	Log likelihood	AIC	BIC
7.04E+09	−802.97	1611.93	1618.36

3.5.5. ARIMA(1,0,0) with Non-Zero Measure

The auto.arima procedure selected an ARIMA(1,0,0) with a non-zero mean as the best ARIMA model. The Ljung-Box test performed on the model's residuals yielded a p-value of 0.47, indicating that the residuals were independently distributed (*i.e.*, like white noise), thus confirming the model's adequacy. The diagnostic plots for the ARIMA model are shown in **Figure 2**. The best ETS model selected was an **ETS(M,N,N)**, indicating a model with multiplicative error, no trend, and no seasonality. The NNETAR model was configured as an **NNAR(3,1,2)**, signifying a network with 3 lagged inputs, 1 hidden layer with 2 nodes, and 20 repetitions to average the results.

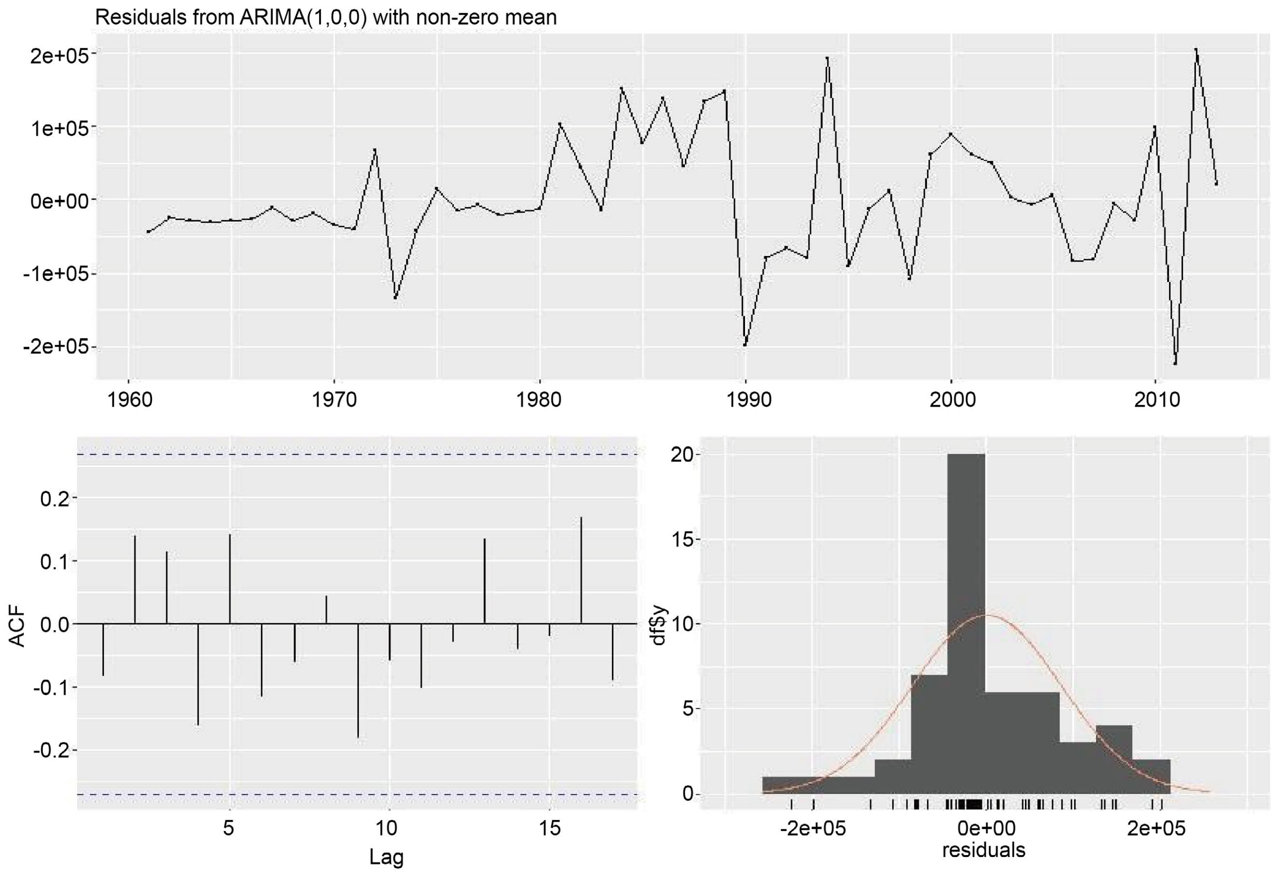

Figure 2. Residual diagnostics for the ARIMA(1,0,0) model (source: World Bank [56]).

3.5.6. Residual Diagnostics for the ARIMA(1,0,0) Model

Figure 2 illustrates the residual diagnostics for the ARIMA(1,0,0) model, serving as a critical visual validation of the linear model's statistical adequacy. The top panel plots the residuals over time, revealing significant variance that mirrors the high volatility periods identified in the historical dataset. The Autocorrelation Function (ACF) plot in the bottom left is particularly significant; it shows that all autocorrelation bars fall within the blue dashed significance limits, confirming that there is no remaining temporal dependence in the error terms—effectively rendering them "white noise". This visual evidence supports the study's Ljung-Box test result ($p = 0.47$), indicating that while the ARIMA model successfully extracted the linear correlations from the series, the large residuals shown in the histogram (bottom right) reflect the model's inability to fully capture the magnitude of the non-linear shocks compared to the neural network models.

The finding that an ARIMA model can be statistically valid (passing diagnostic checks) yet underperform in predictive accuracy compared to AI models is well-supported by recent agricultural forecasting literature. Öztürk and Türkyılmaz (2024) corroborate this, noting that while ARIMA models frequently pass residual diagnostic tests like the ACF, they often fail to capture the structural non-linearities in volatile agricultural markets as effectively as LSTM or ANN models [6]. Ahmar *et al.* (2023) reinforce this distinction, demonstrating in their study of food grains that while ARIMA serves as a robust benchmark with stable residuals, Neural Network Autoregressive (NNAR) models consistently provide superior accuracy in complex biological systems [4]. The necessity of these diagnostic evaluations is emphasized by Majhi *et al.* (2023), who argue that analyzing ACF plots and residual distributions is a prerequisite for validating any time series model applied to cereal price or production indices [10]. Furthermore, the high variance observed in the residual time plot is contextually explained by Abdi *et al.* (2024), who attribute such erratic deviations in Somali crop data to the specific lack of resilience against intensifying climate change impacts [1].

3.5.7. Comparative Forecast Accuracy

Figure 3 presents a multi-panel visual comparison of the eight forecasting models evaluated in the study, plotting their predicted trajectories against the historical cereal production data of Somalia. The visualization reveals a stark contrast in behavioral dynamics between linear and non-linear approaches. The panels for traditional models, such as ARIMA and Theta, display relatively rigid, linear trend extrapolations with rapidly expanding shaded confidence intervals, indicating a high degree of uncertainty and an inability to capture short-term fluctuations. Conversely, the computational intelligence models, specifically the Neural Network Autoregressive (NNETAR) and ANN, exhibit distinct non-linear patterns that attempt to adapt to the historical volatility. This visual assessment reinforces the empirical error metrics (**Table 4**), highlighting that while linear models tend to "smooth out" the data—thereby missing critical structural breaks—the neural

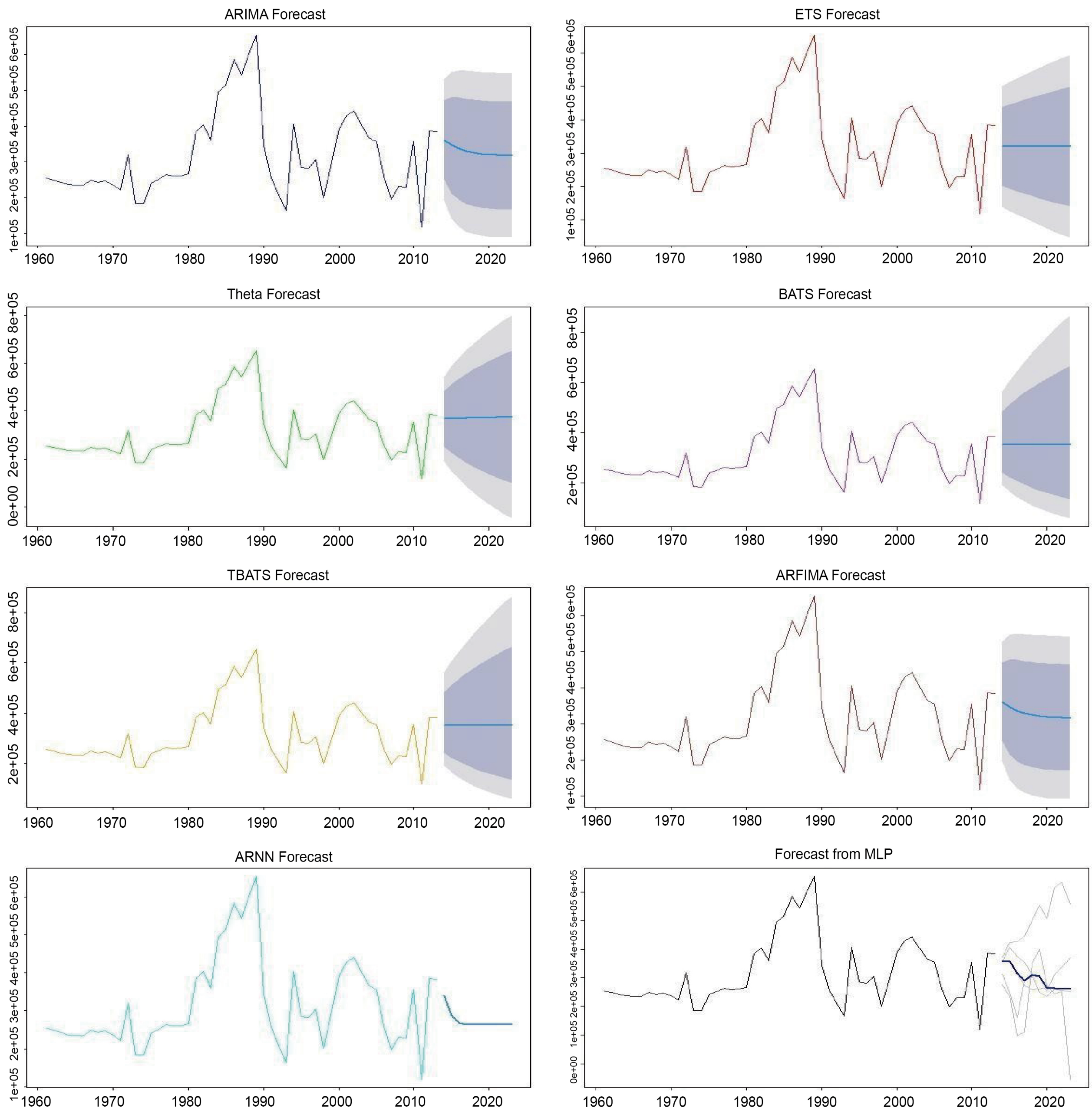

Figure 3. Visual comparison of the forecasts generated by each of the eight models against the historical data (Source: World Bank [56]).

networks provide a more complex projection that better reflects the stochastic nature of the country's rainfall-dependent agriculture. The visual divergence between the static linear forecasts and the adaptive AI-driven projections shown in **Figure 4** is consistent with recent findings in agricultural data science. Öztürk and Türkyılmaz (2024) observed similar visual trends in their comparative study, noting that while ARIMA models produce smooth, mean-reverting forecasts, they visually fail to track the abrupt structural breaks in commodity prices compared to LSTM or Neural Networks [6]. Ahmar *et al.* (2023) reinforce this observation, demonstrating that in comparative plots of food grain data, NNAR models provide a tighter fit to historical oscillations than Holt-Winters or ARIMA, which often fail to react to sudden shifts in the data generating process [4]. The operational necessity of adopting these more complex visual models is contextualized by Sancar (2024), who argues that the "Third Green Revolution" demands moving beyond static descriptive statistics toward dynamic AI models capable of supporting precision agriculture [12]. Finally, the wide confidence intervals observed in **Figure 4** are explained by Abdi *et al.* (2024), who attribute the high unpredictability of the data to the specific lack of climate resilience in Somali staple crops [1].

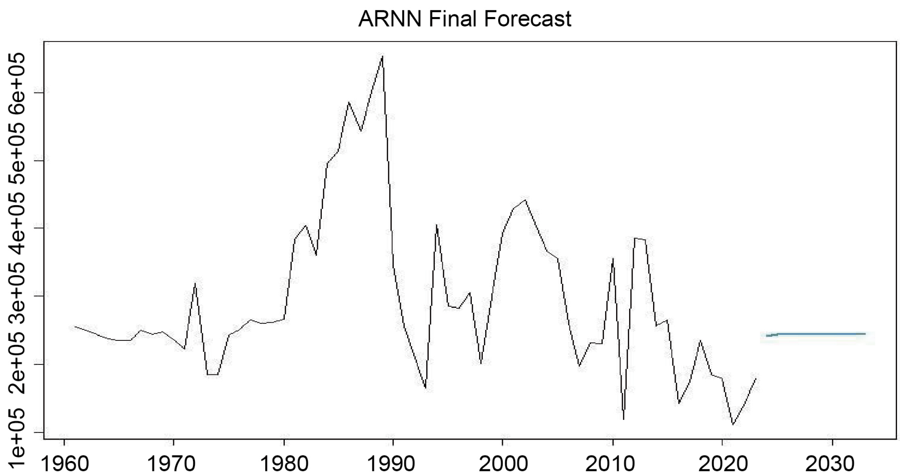

Figure 4. Arnn forecast (Source: World Bank [56]).

3.5.8. Forecast Projections

Forecasted Values (2024-2033) from NNETAR Model:

- **2024:** 240,691 tons;
- **2025:** 243,517 tons;
- **2026:** 243,782 tons;
- **2027-2033:** ~243,810 tons.

Figure 4 visualizes the ten-year forecast for Somali cereal production (2024-2033) generated by the Neural Network Autoregressive (NNETAR) model, which was identified as the study's superior forecasting instrument. The graph displays the volatile historical time series followed by a projected trajectory that stabilizes relatively quickly compared to the erratic past data. The forecast predicts a slow, oscillating recovery, with production estimated to rise marginally from 240,691 tons in 2024 to approximately 243,810 tons by 2033. This stabilization pattern is characteristic of neural networks trained on data lacking a persistent linear trend; it suggests that without significant structural or technological interventions, domestic production will plateau, failing to return to the peak levels observed in the 1980s. The graph effectively serves as an early warning signal, indicating that the status quo will likely result in stagnation rather than robust growth.

The predictive behavior and the methodological validity of the NNETAR model shown in **Figure 4** are strongly supported by recent literature in agricultural data science. Öztürk and Türkyılmaz (2024) corroborate the utility of this approach, finding that Neural Networks consistently outperform linear models like ARIMA in handling the non-linear dynamics of agricultural commodities, although they note that such models often project stability in the absence of strong trend signals [6]. The projected stagnation in production volume is contextually explained by Abdi *et al.* (2024), who attribute the inability of Somali crops to bounce back to historical highs to a fundamental lack of climate resilience [1]. Furthermore, the operational necessity of using such AI-driven forecasts for planning is highlighted by Sancar (2024), who frames predictive analytics as a key component of "Smart Agriculture" needed to secure food systems in developing nations [12]. Finally, Funk *et al.* (2023) emphasize that implementing these tailored forecasts is critical for East Africa to move from reactive crisis management to proactive climate adaptation [34].

The plot shows the historical data series followed by the 10-year point forecast from the best performing NNETAR model, which stabilizes quickly. This pattern is characteristic of neural network models trained on data without a strong, persistent trend.

4. Conclusions

This study successfully conducted a rigorous comparative analysis of linear and non-linear time series models to forecast cereal production in Somalia, a region characterized by extreme climatic volatility and data scarcity. The empirical evidence definitively establishes the Neural Network Autoregressive (NNETAR) model as the superior forecasting instrument, achieving the lowest error metrics (RMSE of 95,426.9 and SMAPE of 40.42%) and significantly outperforming traditional statistical benchmarks such as ARIMA and the Theta model.

The research highlights a critical methodological shift required for agricultural planning in East Africa. The underperformance of linear models (ARIMA, ARFIMA) confirms that traditional econometric assumptions are insufficient for capturing the stochastic nature of Somali agriculture, which is rife with structural breaks caused by drought, flood, and instability. Conversely, the success of the NNETAR model validates the efficacy of computational intelligence in navigating these non-linear dynamics, offering a more robust framework for the "Smart Agriculture" solutions needed in developing nations.

From a policy perspective, the 10-year forecast generated by the NNETAR model (2024-2033) predicts a slow, oscillating recovery in production levels. While positive, this trajectory suggests that without structural intervention, domestic production alone may remain insufficient to meet the demands of a growing population. Therefore, this model should serve as a vital early warning system (EWS) for the Somali government and international aid agencies, facilitating a transition from reactive humanitarian relief to proactive, data-driven food security strategies aligned with SDG 2 (Zero Hunger).

However, the study acknowledges a limitation regarding the systemic bias toward over-forecasting observed across all models during extreme drought periods. This suggests that while univariate analysis provides a strong baseline, future research must move toward multivariate hybrid models. Integrating exogenous variables—such as rainfall indices, temperature anomalies, and conflict data—will be essential to further refine accuracy and fully capture the environmental shocks that define Somalia's agricultural landscape. Ultimately, this research bridges the gap between theoretical data science and practical humanitarian application, demonstrating that advanced AI forecasting is a requisite tool for safeguarding food security in vulnerable economies.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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